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EFFECTS OF PSYCHOLOGICAL CAPITAL AND COGNITION ON STEM LEARNING IN IOT SMART ENERGY-SAVING PROJECTS

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Abstract. *Project-based learning (PBL) plays a critical role in fostering interdisciplinary integration within science, technology, engineering, and mathematics (STEM) education. However, its complexity often hinders students' ability to apply knowledge and solve problems, particularly in environments that lack psychological and cognitive support. This study aims to address these challenges by constructing a STEM education model centered on PBL and examining the interactions among STEM psychological capital (SPC), problem-solving skills (PS), STEM cognition (SC), and STEM project-based learning performance (SP). In total, 230 seventh-grade students participated in a STEM project-based activity themed "Internet of Things (IoT) Smart Energy-Saving House." Data were collected through questionnaires and performance assessments. Partial least squares structural equation modeling (PLS-SEM) was used to analyze the interactions. By validating the interplay among psychological capital, cognition, and problem-solving abilities in STEM-PBL contexts, this study identifies the critical role of SPC, PS, and SC in enhancing students' SP outcomes and underscores the necessity of integrating psychological support and cognitive development into STEM curricula. Furthermore, the findings provide a novel framework for bridging the gap between theoretical knowledge and practical application, offering valuable insights for future research and educational design.*

Keywords: *project-based learning, STEM cognition, problem-solving skills, psychological capital, STEM education, partial least square-structural equation modeling*

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Introduction

Science, technology, engineering, and mathematics (STEM) education is widely recognized as an effective approach to prepare students for the challenges of the 21st century. By encompassing multiple disciplines, STEM education can cultivate critical thinking, innovation, and reasoning skills. However, as demand for STEM education continues to grow, educators and researchers face the challenge of effectively implementing teaching strategies within this complex and interdisciplinary framework. Despite the potential of traditional STEM education, significant issues persist in engaging students, fostering meaningful learning, and assessing educational outcomes, which makes these concerns central to the field (Sulaiman et al., 2023).

A meta-analysis has revealed that project-based learning (PBL) is one of the most effective methods for enhancing learning outcomes (Suciana et al., 2023). PBL has gained traction in STEM education due to its ability to foster innovation, critical thinking, and problem-solving skills (PS) as students attempt to address real-world problems. However, few studies have explored the specific mechanisms through which STEM project-based learning (STEM-PBL) promotes learning, particularly its role in activating cognitive and skill-related processes. From the perspective of cognitive activation theory, Lamb et al. (2015) have suggested that the success of STEM learning may rely on an interplay between emotional and cognitive factors. Creating such interplay activates cognitive processes, enhancing the ability of students to apply and integrate disciplinary knowledge. The interaction between cognition and other critical elements also deepens understanding of STEM disciplines and enables students to deploy essential skills when confronted with complex problems.

Consequently, STEM education aims to equip students with the skills necessary to address complex interdisciplinary challenges, yet it simultaneously presents urgent difficulties. While the integration of science, technology, engineering, and mathematics offers students diverse opportunities for learning, many struggle to connect abstract concepts with real-world applications, resulting in a disconnect between learning and practice. Addressing this gap requires a deeper exploration of the interplay between psychological

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and cognitive factors in the learning process. Therefore, elements from the Cognition-Priming Model (CPM) and STEM psychological capital (SPC) have been integrated to develop an innovative framework for elucidating the mechanisms underlying student success in STEM-PBL.

A CPM can serve as a robust framework for understanding cognitive processes, specifically the interactions between external stimuli and internal cognition at the core of learning. Lamb et al. (2014) have noted that embedding specific contexts or activities within educational design can effectively trigger cognitive processes, helping students to apply knowledge in analysis and problem-solving tasks. These cognitive processes often manifest externally in the form of behaviors or outcomes, such as test responses or project performance (Bogg & Finn, 2010).

SPC has been incorporated into a CPM as an extended framework. SPC includes critical psychological traits, including passion, perseverance, hope, optimism, and resilience, which play a pivotal role in helping students navigate STEM learning challenges (Blanchette & Richards, 2010). This research hypothesized that SPC would enhance learner capacity to respond to external learning stimuli, for example by facilitating more active engagement in challenging tasks or leveraging relevant background knowledge, thereby supporting cognitive priming processes and consequently improving PS and learning performance. Furthermore, embedding these cognitive and psychological mechanisms within practical, interdisciplinary contexts—such as technology-driven solutions to real-world problems—could amplify their impact, aligning STEM education with broader societal needs.

Given the increasing global demand for sustainable education practices in STEM, particularly in regions facing energy efficiency challenges, there is a need for structured frameworks that incorporate both cognitive and psychological dimensions. While project-based learning has been widely recognized as an effective pedagogical approach, its implementation often lacks a systematic model that fosters interdisciplinary problem-solving and resilience. By integrating IoT technology and psychological support, this study proposes a replicable framework that educators can adapt to cultivate essential 21st-century skills while addressing sustainability challenges.

Thus, this study aimed to construct and validate a STEM-PBL model that examined the interplay among SPC, PS, SC, and SP. The research provided empirical insights into the cognitive and psychological mechanisms underlying students' project-based learning performance.

Literature Review

Conceptualization of STEM Psychological Capital

Psychological capital (PC) can be defined as a positive psychological developmental state and traditionally encompasses four core dimensions: self-efficacy, hope, optimism, and resilience (Luthans et al., 2007). According to the broaden-and-build theory (Fredrickson, 2001), positive emotional experiences expand thought-action repertoires and build enduring psychological resources. PC is considered a measurable, developable, and effective resource; it is known to enhance academic and organizational performance and to play a critical role in academic success (Avey et al., 2011; Li et al., 2023; Ortega-Maldonado & Salanova, 2018).

As STEM education continues to evolve, learners face increasingly complex challenges including long-term commitment, integration of multidisciplinary knowledge, and demand for advanced PC. Sweetman et al. (2011) found that PC has a direct and significant effect on creativity and suggested that the integrative role of PC is crucial in cognitive tasks, particularly those involving complex problem-solving. PC enhances focus, strategic thinking, and goal-oriented behaviors, all of which are essential for addressing such challenges. In general, creativity and complex problem-solving share similar cognitive characteristics: both require substantial psychological resources, and positive psychological states are known to enhance problem-solving performance (Luthans et al., 2011).

Moreover, Luo et al. (2024) explored how STEM capital, its significant influence on learners' academic performance and aspirations in STEM-related disciplines. Their findings indicated that STEM capital has significant effects on long-term commitment to achieving STEM-related goals, confirming the importance of social support and learning resources to STEM capital, but the study did not sufficiently explore how the intrinsic psychological traits of learners affect PBL. Considering that PBL requires learners to demonstrate a high level of autonomy and sustained engagement, it is proposed that the conventional PC should be further refined to address the specific demands of STEM-PBL contexts.

Therefore, this framework retains the core constructs of traditional PC (hope, optimism, resilience) while introducing two additional constructs – passion and perseverance – to comprehensively capture the psychological needs and behavioral expressions of students engaged in STEM-PBL. Self-efficacy remains central to traditional PC and plays a vital role in helping learners tackle specific challenges in STEM contexts (Schunk & DiBenedetto, 2020),

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but a sole focus on self-efficacy may not fully account for the emotional drive and behavioral persistence among learners as they engage in the long-term processes and multi-stage challenges involved in PBL.

Compared to existing research, this study is the first to incorporate passion and perseverance into the PC framework and integrate the CPM to examine their unique roles in STEM-PBL. This innovation expands the theoretical application of PC, also addresses a critical gap in PBL research concerning the impact of students' psychological traits. Passion is linked with deep interest and intrinsic motivation among learners as they pursue goals, particularly those related to real-world problems. Perseverance is linked with consistent effort and long-term engagement, particularly as learners engage in iterative trial-and-error processes (Duckworth et al., 2007). These attributes enhance the adaptability of the PC framework to the specific demands of STEM-PBL, offering a more nuanced understanding of learner behaviors.

Passion

Passion is linked with a learner's intrinsic motivation and sustained interest in achieving a goal. It is critical to maintaining long-term engagement in solving complex problems; particularly within STEM education, addressing real-world challenges often demands strong intrinsic drive. Duckworth et al. (2007) found that passion and perseverance are significant predictors of academic achievement and success in other fields. Passion encourages learners to be more autonomous and creative in projects while sustaining learning motivation over time. Vallerand (2015) noted that passion fosters psychological adaptability, helping learners remain consistently committed to long-term goals. This trait is particularly vital in PBL environments that require iterative trial and error as well as prolonged focus. The combination of passion and learning objectives encourages learners to actively engage in the learning process and to demonstrate higher levels of creativity and resilience in challenging situations. Learners with passion achieve superior long-term performance, particularly when tackling demanding tasks that require innovative solutions and unwavering dedication.

Perseverance

Perseverance is linked with determination and consistent effort to overcome learning challenges, especially within STEM learning environments that require iterative trial-and-error and continuous improvement. Some research suggests a modest direct correlation between perseverance and academic achievement, but the long-term effects appear to be significant. Perseverance enhances the completion rate of problem-solving tasks and the quality of learning, particularly in PBL. Luthans et al. (2018) reported that high-perseverance learners are better equipped to handle setbacks and challenges in the learning process, as their self-regulation and reflective abilities can deepen and integrate cognitive processes.

Hope

Hope is a psychological trait that drives learners to set goals and actively seek methods to achieve them. Snyder et al. (2002) conceptualized hope as a combination of "pathways thinking" and "agency thinking." From this perspective, high-hope learners can remain flexible in the face of challenges, continuously exploring alternative strategies to overcome obstacles. Hope is an important element of PC, significantly contributing to goal attainment and improved learning performance (Luthans et al., 2004). High-hope learners tend to set clear and challenging goals, view setbacks as opportunities for growth, and break down goals into manageable steps, resulting in greater academic success (Snyder et al., 2006). In contrast, low-hope learners often set vague or easily achievable goals, struggle with flexibility, and are prone to negativity when encountering difficulties. Hope plays a critical role in shaping goal-setting quality, coping strategies, and sustained engagement.

Optimism

Optimism refers to a tendency to attribute future outcomes to positive events, particularly when facing challenges. Peterson (2000) noted that optimists perceive difficulties as surmountable challenges and believe in their ability to find solutions. Optimism reduces psychological stress, enhances persistence, and sustains motivation in learning. In the context of STEM-PBL, optimistic learners maintain a positive attitude during iterative trial-and-error processes, ultimately achieving successful outcomes. Carver et al. (2010) found that optimism is closely linked with

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coping strategies and psychological well-being, significantly affecting performance under challenging conditions. Bertieaux et al. (2024) identified optimism as a key factor of PC, underscoring its importance in supporting STEM learners.

Resilience

Resilience refers to the ability of learners to quickly adapt and reconstruct strategies when faced with failure or difficulty. Smith et al. (2013) found that resilience helps learners manage stress in challenging situations and also to extract valuable lessons from mistakes and refine their learning strategies. In PBL contexts, resilient students are more able to adapt to uncertainties in knowledge application and tend to demonstrate creative PS during reflection and improvement; Masten (2001) identified resilience as a critical factor for maintaining adaptive functioning in adversity, with profound implications for learning and development. Resilience is generally considered a vital psychological resource (Luthans et al., 2004).

Problem-Solving Skills, STEM Cognition, and STEM Project-Based Learning Performance

One core objective of STEM education is to foster interdisciplinary problem-solving. Sternberg (2003) conceptualized PS as involving key stages such as problem identification, data collection and analysis, solution design and implementation, and reflection and improvement, forming a comprehensive learning and thinking process. This ability is particularly critical in STEM education, as students must integrate elements of mathematics, science, and technology to address diverse real-world challenges.

PS and SC are closely linked. English (2023) reported that STEM-based problem-solving promotes the development of richer disciplinary thinking in mathematics and technology-related fields, enhancing ability to integrate knowledge across disciplines. Conversely, Su (2020) noted that a lack of higher-order cognitive skills limits the ability of students to integrate STEM knowledge, thereby undermining their performance in applying this knowledge to interdisciplinary contexts. Ultimately, this deficiency can hinder their potential to develop robust problem-solving capabilities.

Lou et al. (2011) found that PBL strategies significantly improve the ability of students to integrate STEM knowledge and positively influence their attitudes about science. These findings suggest that students engaging in iterative cycles of knowledge acquisition and solution implementation may have a deeper understanding of STEM-related knowledge and also internalize related concepts for more flexible applications. This iterative process improves conceptual understanding, also equips students with the skills to achieve superior performance in project-based tasks.

The role of SC as a mediator between PS and SP further underscores its importance. SC supports the cognitive processes involved in PS and also bridges the gap between problem-solving and project-based outcomes. Stohlmann et al. (2012) noted that SC facilitates the application of abstract STEM knowledge to practical tasks, enabling students to refine their problem-solving strategies and enhance their project outcomes. This suggests that the interaction between PS and SP is strengthened when SC is effectively developed. For instance, students with a strong grasp of STEM concepts are better equipped to identify gaps in their solutions and iteratively improve their designs, leading to superior performance in PBL environments.

STEM Project-Based Learning

Thomas et al. (1999) stressed that fostering autonomous learning and practical abilities is at the core of PBL. As students engage in the process of solving real-world problems, this learning model emphasizes the transformation of theoretical knowledge into concrete solutions, promoting higher-order thinking and knowledge construction (Kokotsaki et al., 2016). PBL is particularly well-suited to STEM education, where the integration of knowledge across multiple disciplines is essential (Asghar et al., 2012; Lin & Lu, 2018). In STEM contexts, PBL provides a practical platform for students to apply disciplinary knowledge in authentic scenarios, enhancing both learning motivation and PS (Capraro et al., 2013; Pertiwi et al., 2024).

During PBL, learners go through iterative cycles of problem identification, solution design, implementation, and reflection. This process effectively promotes the development of PS. The PBL learning process requires mastering disciplinary knowledge, as well as higher levels of psychological resilience. For example, traits such as passion,

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perseverance, hope, optimism, and resilience play a crucial role in determining the quality of task completion and overall learning outcomes when students face repeated trials and challenges (Duckworth et al., 2007; Luo et al., 2024).

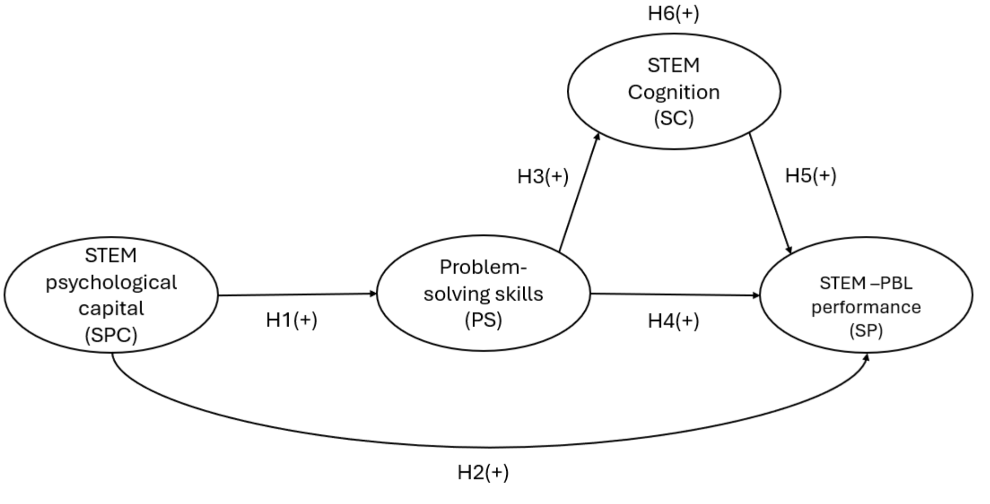
However, the underlying mechanisms of its effectiveness remain underexplored, as do the applications of SPC in PBL. The core constructs of SPC (hope, optimism, and resilience) closely align with the multifaceted learning scenarios of PBL. For example, authentic challenges encountered during PBL can trigger increased motivation and psychological adaptability in learners, thereby supporting improved learning outcomes (Luthans et al., 2004). These psychological traits can act as critical enablers in navigating the complexities and uncertainties inherent in PBL, fostering academic success and also the development of durable skills for interdisciplinary problem-solving.

Research Model and Hypotheses

The literature review discussed above revealed that current CPM applications primarily focus on general cognitive and emotional priming mechanisms, with limited exploration of applications in STEM-specific educational contexts, particularly the role of PC in learning processes. This research gap highlights the need to examine the role of SPC in PBL. Therefore, CPM was integrated with PS and SC to examine their combined influence on learning outcomes. Figure 1 presents the interactions between these constructs and their effects on student performance in STEM-PBL.

- H1: Students' STEM psychological capital (SPC) has a positive effect on their problem-solving skills (PS).
- H2: Students' STEM psychological capital (SPC) has a positive effect on their STEM project-based learning performance (SP).
- H3: Students' problem-solving skills (PS) have a positive effect on their STEM cognition (SC).
- H4: Students' problem-solving skills (PS) have a positive effect on their STEM project-based learning performance (SP).
- H5: Students' STEM cognition (SC) has a positive effect on their STEM project-based learning performance (SP).
- H6: Students' problem-solving skills (PS) have an indirect effect on their STEM project-based learning performance (SP) via STEM cognition (SC).

Figure 1
Research Model



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Research Methodology

General Background

This study utilizes the design and construction of an IoT smart energy-saving house as an educational setting to examine the key factors influencing students' learning processes within the STEM-PBL framework. A quantitative approach was employed, with data collected using a Likert 7-point scale, incorporating the SPC scale, PS scale, and performance assessments comprising SC scores and SP scores. These instruments are designed to comprehensively evaluate students' performance in terms of psychological support, PS, knowledge comprehension, and practical skills, thereby providing empirical evidence from this study on students' STEM learning outcomes.

Participants

This project was conducted from January to May 2021 at a lower-secondary school in Taoyuan City, Taiwan, an institution renowned for its long-standing implementation of interdisciplinary STEM education and high-quality curriculum. The curriculum is distinguished by two notable features: (1) it received an award in a national teaching plan competition, underscoring the excellence of its educational design; and (2) it has been incorporated into textbooks, reflecting its exemplary status in STEM education. Compared to other schools, this curriculum demonstrates a more proficient integration of STEM teaching and learning components, offering a representative sample of students for this study. The IoT smart energy-saving house course was designed for seventh-grade students and spanned 15 weeks. Participation was voluntary, with students informed in advance of their right to withdraw at any time without consequences. To ensure anonymity, participant data were managed using unique identifiers rather than names. After data collection, 26 invalid responses were excluded, yielding a valid response rate of 90%. Missing data were addressed using the median imputation method, resulting in a final sample of 230 students (N = 230), comprising 110 males (48%) and 120 females (52%), as detailed in Table 1.

Table 1
Research Participant Data

Gender	*N*	%
Male	110	48
Female	120	52
Total	230	100

Procedures

An educational model centered on STEM-PBL was constructed. It involved a 15-week period of planned activities that can be divided into two main components, as shown in Table 2.

Table 2
Overview of STEM-PBL Activities

Activity	Course Focus	Course Content	Duration
Cognitive Learning in Technology and Mathematics	Developing foundational knowledge and technical skills.	• Safe operation and use of common hand tools (e.g., soldering irons, coping saws, pliers). • Drawing 3D diagrams with dimensions and annotations. • Understanding machining workflows.	5 weeks: Construction of wooden speakers. 6 weeks: Woodworking and soldering
STEM Project-Based Practical Learning	Applying interdisciplinary knowledge to solve real-world problems.	• IoT concepts and experimental design. • Designing and building IoT smart energy-saving house. • Prototyping, testing, and improving designs iteratively.	4 weeks

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Figure 2-4 presents the practical learning activity. The educational process was guided by the 6E educational model proposed by Burke (2014), with the following phases:

1. Engage:
   Students were introduced to the concept of smart home control systems in everyday life. They explored the key components required to build an IoT system, including devices, sensors, networks, and IoT services.
2. Explore:
   Educational content expanded to include how IoT devices can sense environmental factors around the energy-efficient house, such as temperature and humidity, along with data collection for analysis and control.
3. Explain:
   Teachers facilitated discussions explaining the role of IoT devices in monitoring and managing environmental conditions. Students gained insights into how data collected by IoT sensors can be used to optimize energy efficiency.
4. Engineer:
   Students constructed a comfortable and energy-efficient house, combining theoretical knowledge with practical implementation. During this phase, they applied what they had learned from hands-on activities to integrate IoT concepts into functional designs.
5. Enrich:
   Learning was deepened through activities that encouraged students to control and provide feedback on the functionality of the house. For example, students worked on keeping the environment within the house at an optimal comfort level by monitoring and adjusting devices.
6. Evaluate:
   The evaluation phase employed diverse methods to assess student performance. Open-ended discussion questions were included in the activity worksheets, prompting students to collaborate in groups, search for information online, and synthesize diverse perspectives. The final outputs included organized data, illustrated designs, and presentations.

Figure 2
IoT Smart Energy-Saving House (Front View)

Note. The image illustrates the front design of an IoT smart energy-saving house, showcasing its architectural features, including a balcony, and greenery. Source: https://reurl.cc/A6bM6p.

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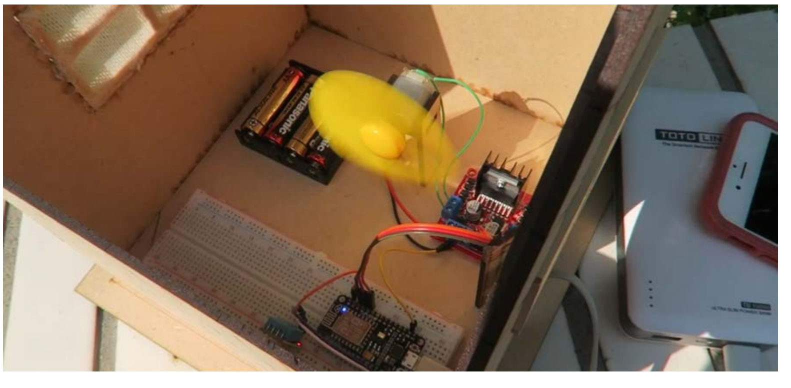
Figure 3
IoT Smart Energy-Saving House (Side View)

Note. The image depicts the external design of an IoT smart energy-saving house, highlighting solar panels and structural features. Source: https://reurl.cc/A6bM6p.

Figure 4
IoT Smart Energy-Saving House (Interior View)



Note. The image shows the internal setup of an IoT smart energy-saving house, featuring electronic components and control systems. Source: https://reurl.cc/A6bM6p.

Instruments

1. The students' SPC scale

This scale was based on the PC framework set out by Luthans and Youssef (2007), which includes four dimensions: hope, optimism, and resilience, with an additional focus on passion and perseverance to be more applicable to the STEM educational model. It was to explore how lower-secondary school students exhibit confidence and sustained effort when faced with complex problem-solving scenarios. Drawing from Duckworth (2009), this scale comprises 10 items (e.g., "I don't give up easily, even when faced with setbacks").

The SPC scale as a measurement tool was administered through a survey method. The SPC scale consists of 22 items, rated on a 7-point Likert scale ranging from 1 ("Not at all like me") to 7 ("Very much like me"). To ensure the content validity of the scale, we invited experts in educational psychology and STEM education to review the

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items. Based on their feedback, we revised the items to improve clarity and relevance (e.g., "When faced with difficulties in learning, I can find various ways to solve the problems" and "I don't give up easily during STEM project activities, even when faced with setbacks") (see Appendix 1). Items with factor loadings below .5 were removed through confirmatory factor analysis.

The validated SPC scale demonstrated reliability and validity, including composite reliability (CR) = .86, average variance extracted (AVE) = .56, and discriminant validity meeting the criteria of AVE square root being greater than the construct's correlations with other constructs (Fornell & Larcker, 1981). The final SPC scale includes 22 items.

2. The students' PS scale

This scale was modified from the problem-solving model proposed by Khunyakari (2015). It measures problem-solving processes and abilities, with higher scores indicating stronger skills. The PS scale was reviewed by experts to improve its validity; the final scale contains 23 items (e.g., "I can analyze the resources and constraints needed to solve a problem") rated on a 7-point Likert scale, ranging from 1 ("Strongly disagree") to 7 ("Strongly agree") (see Appendix 2).

The validated PS scale demonstrated reliability and validity, including (CR = .92), (AVE = .70), and discriminant validity meeting the Fornell and Larcker (1981) criteria.

3. The students' SC scores

Students' SC scores reflect their performance in mathematics and life technology tasks, such as using a coping saw and completing speaker projects. Unlike conventional academic assessments, these tasks emphasize students' ability to integrate interdisciplinary knowledge and apply it to practical problem-solving.

In PBL, students utilize mathematical knowledge in various ways, including data collection, model building, and result analysis. These activities demonstrate their understanding of mathematical concepts and also highlight their ability to apply them to real-world problems. Similarly, real-world challenges demand practical skills and technological applications. For instance, in the coping saw and speaker tasks, students design and construct products that meet specific project requirements. This process requires the integration of material science principles, technical operations, and design thinking, fostering both creativity and problem-solving skills. The validated SC tool demonstrated reliability and validity, with a CR of .79 and an AVE of .66, meeting the criteria for construct reliability (Fornell & Larcker, 1981).

4. The students' SP scores

The STEM project-based activity, themed "IoT Smart Energy-Saving House" aimed to foster students' understanding and application of IoT technologies through the practical implementation of an energy-saving house. The course overview centers on the design and construction of an IoT smart energy-saving house, where students acquire skills in utilizing electronic components, circuit design, and web applications (e.g., ThingSpeak) to integrate technologies for energy conservation. The educational process encompasses comprehending green building metrics, fostering collaboration and innovation, and programming and hands-on implementation, reinforced through group collaboration and empirical data analysis to deepen learning.

The assessment of student performance comprises three key dimensions: First, the knowledge domain evaluates students' grasp of IoT technologies and energy-saving concepts, such as the application of green building metrics. Second, practical competence examines the feasibility and effectiveness of the energy-saving house model, evidenced by data such as humidity levels and fan operation records. Third, the presentation of outcomes assesses students' ability to organize their inquiry process using mind maps and demonstrate creativity. This multifaceted evaluation ensures a comprehensive measure of both theoretical understanding and practical proficiency.

The validated SC scores demonstrated strong reliability and validity, with a CR of .80 and an AVE of .67, meeting the criteria for construct reliability (Fornell & Larcker, 1981).

Data Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2017) was employed to assess the associations between latent independent and dependent variables, identifying potential factors influencing STEM

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project performance. This method is considered suitable for the research due to its reduced reliance on normal distribution assumptions, rendering it appropriate for the sample size (Ünal & Uzun, 2021). Based on previous research, the SPC and PS scales were utilized, and a structural equation model (SEM) was applied to validate the hypotheses. All collected data were summarized for analysis, and confirmatory factor analysis was conducted to verify the validity and reliability of the measures.

Research Results

This study aimed to construct an educational model centered on PBL by employing PLS-SEM to assess the reliability and validity of the research model. Following the two-step SEM analysis process, the measurement model was first evaluated for reliability and validity through confirmatory factor analysis, examining items' factor loadings, Cronbach's alpha values, composite reliability (CR) values, and average variance extracted (AVE). Subsequently, the structural model was analyzed to test the hypothesized paths and explanatory power of the variables.

Measurement Model

In PLS-SEM, constructing higher-order models can be approached using either the repeated indicators method or the two-stage approach. Hair et al. (2021) note that the reflective–reflective model is better suited for the repeated indicators method. Because the SPC and PS scales in this study utilized a reflective-reflective model, the repeated indicators method was deemed the more appropriate choice for model construction.

Previous research was built upon (Hair et al. 2021; Wetzel & Wigfield 2009) by establishing first-order constructs. Next, indicators were assigned to corresponding higher-order constructs, and the associated paths were defined. The SPC model includes five constructs: Passion, Perseverance, Hope, Optimism, and Resilience. The final SPC scale consists of 22 items (Table 3), and the PS scale has 23 items, with both scales demonstrating strong reliability and validity (Table 4).

As shown in Table 3, the SPC scale was refined by removing items s1, s18, s19, and s26 due to factor loadings below .5. Next, the scale was reevaluated, and all factor loadings were stable and exceeded .60. The CR value was .86, above the threshold of .6, indicating good internal consistency. The AVE value was .56, higher than the threshold of .5, reflecting strong convergent validity. Furthermore, the square root of AVE values was greater than the inter-construct correlations, confirming discriminant validity.

Table 3
Item Factor Loadings, CR, Cronbach's Alpha Values, and Descriptive Statistics of the SPC Scale

Instrument variables and measurement items			Factor loadings	M (SD)	Cronbach's α	CR	AVE
Second-order constructs	First-order constructs	Item					
SPC	-	-	-	-	.80	.86	.56
	Passion	-	-	-	.70	.81	.52
		s2	.72	3.60 (1.26)			
		s3	.81	5.10 (1.46)			
		s4	.72	4.60 (1.32)			
		s5	.63	5.50 (1.22)			
	Perseverance	-	-	-	.85	.89	.63
		s6	.84	4.70 (1.59)			
		s7	.70	5.00 (1.28)			
		s8	.77	4.80 (1.52)			
		s9	.86	5.00 (1.29)			
		s10	.78	4.80 (1.55)			
	Hope	-	-	-	.87	.90	.60

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Instrument variables and measurement items			Factor loadings	M (SD)	Cronbach's α	CR	AVE
Second-order constructs	First-order constructs	Item					
		s11	.79	4.80 (1.41)			
		s12	.78	5.40 (1.21)			
		s13	.82	5.40 (1.27)			
		s14	.80	5.20 (1.26)			
		s15	.70	5.20 (1.28)			
		s16	.77	4.50 (1.47)			
	Optimism	-	-	-	.84	.89	.68
		s17	.60	4.70 (1.68)			
		s20	.92	4.90 (1.26)			
		s21	.93	5.00 (1.69)			
		s22	.87	4.70 (1.68)			
	Resilience	-	-	-	.81	.89	.73
		s23	.84	4.70 (1.69)			
		s24	.81	5.20 (1.46)			
		s25	.90	4.40 (1.80)			

Note. AVE = Average variance extracted, *CR* = Composite reliability

The measurement model for the PS scale demonstrated reliability and validity after factor analysis, as shown in Table 4. All loadings consistently exceeded .69, indicating strong indicator reliability. The CR values were all above .93, reflecting excellent internal consistency among the constructs. The AVE values were greater than .69, surpassing the recommended threshold of .50, which confirms good convergent validity. Moreover, the square roots of each AVE value were greater than the inter-construct correlations, supporting the discriminant validity of the model. These results confirm that the measurement model possesses adequate reliability and validity.

Table 4
Item Factor Loadings, CR, Cronbach's Alpha Values, and Descriptive Statistics of PS

Instrument variables and measurement items			Factor loadings	M (SD)	Cronbach's α	CR	AVE
Second-order constructs	First-order constructs	Item					
PS	-	-	-	-	.91	.93	.69
	Defining and analyzing				.77	.87	.68
		p1	.82	5.26 (1.15)			
		p2	.81	5.24 (1.17)			
		p3	.85	4.93 (1.14)			
	Collecting and analyzing data	-	-	-	.80	.88	.71
		p4	.84	5.30 (1.18)			
		p5	.85	5.53 (1.20)			
		p6	.83	5.27 (1.14)			
	Developing design ideas	-	-	-	.83	.88	.59
		p7	.74	5.40 (1.34)			
		p8	.80	5.08 (1.32)			
		p9	.74	5.42 (1.33)			
		p10	.80	4.83 (1.25)			
		p11	.77	4.86 (1.16)			

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Planning for making	-	-	-	.74	.84	.56
	p12	.68	4.83 (1.43)			
	p13	.81	5.19 (1.22)			
	p14	.78	5.17 (1.15)			
	p15	.72	5.33 (1.23)			
Making products	-	-	-	.82	.87	.58
	p16	.76	5.70 (1.08)			
	p17	.71	6.28 (0.94)			
	p18	.77	5.78 (1.20)			
	p19	.84	5.93 (1.09)			
	p20	.73	4.93 (1.24)			
Testing, evaluating, and revising solutions	-	-	-	.82	.89	.73
	p21	.83	5.21 (1.25)			
	p22	.91	5.19 (1.27)			
	p23	.83	4.83 (1.32)			

Note. AVE = Average variance extracted, *CR* = Composite reliability

Structural Model

PLS-SEM was employed to examine the associations among SPC, PS, SC, and SP. A collinearity diagnosis was conducted, with variance inflation factor (VIF) values ranging from 1.12 to 3.43, all below the threshold of 5. These findings indicated that collinearity among variables in the structural model was not severe and did not affect the estimation of path coefficients (Hair et al., 2021). To test the hypothesized interactions, a bootstrapping procedure was performed with 5000 random subsamples to evaluate the significance of the hypotheses (Hair et al., 2021). For PLS-SEM, the structural model's quality can be assessed using two key indicators: predictive capability (including path coefficient significance and predictive relevance [Q^2]) and explanatory capability (including explained variance [R^2] and effect size [f^2]).

As shown in Figure 5, the interactions among constructs can be examined through β coefficients, the significance of path coefficients (*p*-values), and corresponding *t*-values, which collectively determine the predictive effects between constructs. The predictive ability of each construct was evaluated: the results revealed that path coefficients for Hypothesis 1 (H1), Hypothesis 4 (H4), Hypothesis 5 (H5), and Hypothesis 6 (H6) were significant, supporting these hypotheses. However, Hypothesis 2 (H2) and Hypothesis 3 (H3) were not supported.

1. H1:

SPC predicted PS in lower-secondary school students. The results revealed that SPC had a significant positive predictive effect on PS ($\beta = .72$, $t = 21.42$, $p < .001$). This suggested that higher levels of SPC were associated with stronger PS in lower-secondary school students. Therefore, H1 was supported.

2. H2:

SPC predicted SP in lower-secondary school students. The results showed no significant positive predictive effect of SPC on SP ($\beta = .10$, $t = 1.18$, $p > .05$). Hence, H2 was not supported.

3. H3:

PS predicted SP in lower-secondary school students. The results revealed that PS showed no significant positive predictive effect on SP ($\beta = .09$, $t = 1.08$, $p > .05$). This suggested that higher levels of PS were associated with better SP. Hence, H3 was not supported.

4. H4:

PS predicted SC in lower-secondary school students. The results demonstrated a significant positive predictive effect of PS on SC ($\beta = .15$, $t = 2.42$, $p < .05$). This indicated that stronger PS were associated with higher levels of SC in lower-secondary school students. Therefore, H4 was supported.

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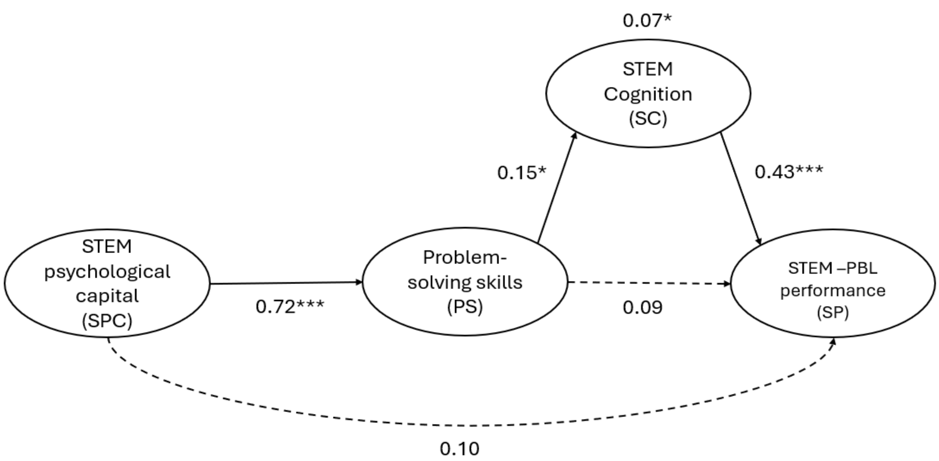
5. H5:

SC predicted SP in lower-secondary school students. The findings revealed a significant positive predictive effect of SC on SP ($\beta = .43$, $t = 7.88$, $p < .001$). This suggested that higher levels of SC were associated with better SP. Hence, H5 was supported.

Figure 5
*Hypothesized Research Model. *p < .05, **p <. 001.*



Following the recommendations of Hair et al. (2021), the predictive relevance of reflective endogenous constructs and their indicators can be assessed using the Stone-Geisser Q^2 value (Geisser, 1974; Stone, 1974). If the Q^2 value exceeds 0, the structural model demonstrates predictive relevance for that construct (Hair et al., 2021). As shown in Table 5, all Q^2 values were greater than 0, indicating the model's predictive relevance. Beyond predictive relevance, the explanatory power of the model was also assessed. The most commonly used indicator for assessing model quality is the coefficient of determination (R^2), which represents the squared correlation between the actual and predicted values of a specific endogenous construct. R^2 measures the extent to which the variance in an endogenous construct is explained by its exogenous predictors. According to Hair et al. (2021), R^2 values close to 0.25 indicate weak explanatory power, values near 0.50 indicate moderate explanatory power, and values approaching 0.70 reflect strong explanatory power.

The R^2 value for the PS construct ($R^2 = 0.52$) indicated moderate explanatory power, the SC construct, with an R^2 value of 0.02, indicated weak explanatory power, and the SP construct ($R^2 = 0.24$) also indicated weak explanatory power. Overall, the conceptual model achieved a moderate level of explanatory capability.

Table 5
Predictive Relevance and Explained Variance

Construct	R^2	Q^2
PS	0.52	0.35
SC	0.02	0.01
SP	0.24	0.14

Note. PS: Problem-solving skills, SC: Cognition, SP: STEM project-based learning performance.

Further analysis of the explanatory effect size (f^2) of each variable provided additional insights, as shown in Table 6. The f^2 value represents the change in R^2 when a specific exogenous variable is removed from the model, indicating its contribution to the explanation of the endogenous variable. According to Cohen's (1988) f^2 guidelines, an effect size is categorized as small when the value falls between 0.02 and 0.15, moderate between 0.15 and 0.35, and large when the value exceeds 0.35.

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The value for the explanatory effect size of SPC was 1.07, signifying a large effect with significant explanatory power. In contrast, the effect sizes of SPC on SP and PS on SP were minimal, suggesting a very limited contribution of these variables to the outcome variable. The effect size of PS on SC was small, while that of SC on SP was moderate, indicating a stronger explanatory contribution.

Regarding model fit, the standardized root mean square residual (SRMR) was examined: for PLS-SEM, an SRMR value between .08 and .10 is considered acceptable (Wang & Wang, 2012). The SRMR for our model was .10, indicating an acceptable level of model fit.

Table 6
Results of Hypothesis Testing

Hypothesis		β	t	f^2	Decision	CILL	CIUL
H1	SPC→PS	.72**	21.12	1.07	Supported	0.65	0.78
H2	SPC→SP	.10	1.18	0.01	Rejected	-0.06	0.27
H3	PS→SC	.09	1.08	0.01	Rejected	-0.08	0.27
H4	PS→SP	.15*	2.42	0.02	Supported	0.03	0.28
H5	SC→SP	.43**	7.88	0.23	Supported	0.32	0.53

Note. SPC: STEM psychological capital; PS: Problem-solving skills; SC: STEM cognition; SP: STEM project-based learning performance; CILL, Confidence interval lower limit; CIUL, Confidence interval upper limit; *p < .05, **p < .001.

Mediating Role of STEM Cognition

Mediation analysis revealed that SC mediated the interaction between PS and SP with a significant indirect effect, as shown in Table 7. Next, the Variance Accounted For (VAF) was calculated to determine the proportion of the indirect effect relative to the total effect. The VAF value was 44.75%, which falls within the acceptable range of 20% to 80%, indicating partial mediation.

These findings suggested that among lower-secondary school students, PS positively predicted SP partly through SC. These results underscored the critical role of knowledge acquisition in mathematics and technology during STEM project learning processes that emphasize problem-solving. These results supported the assumptions of the CPM, highlighting the facilitative role of SC in linking PS to SP.

Table 7
Mediation Tests

Hypothesis	Independent variable→ dependent variable	Intervening variable	Direct effect	Indirect effect	Total effect	VAF	Decision
H6	PS→SP	SC	0.09 (1.08)	0.07* (2.23)	0.16 (1.62)	44.75%	Supported

Note. PS: Problem-solving skills, SC: STEM cognition, SP: STEM project-based learning performance. *p < .05

Discussion

Predictive Effect of SPC on PS and SP

SPC is an innovative construct that includes hope, optimism, resilience, passion, and perseverance. Previous research has confirmed that traditional PC and the concepts of perseverance and passion significantly influence high-order abilities, such as creativity, and have measurable effects on academic performance (Avey et al., 2011; Duckworth et al., 2007; Li et al., 2023; Ortega-Maldonado & Salanova, 2018; Sweetman et al., 2011). Our findings indicate that SPC positively predicts PS, highlighting its critical role in fostering high-order learning capabilities. They support Fredrickson's (2001) broaden-and-build theory, which emphasizes how positive PC enables students to overcome challenges and sustain long-term learning motivation. Students with high levels of PC are better

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equipped to convert positive emotions into the drive to solve problems, thereby enhancing their creativity and sustained engagement.

It is important to note that the predictive role of SPC in SP is not yet fully established, although student PC may indirectly influence academic outcomes (Ortega-Maldonado & Salanova, 2018) and appears to play a mediating role in the association between positive emotions and academic performance (Carmona-Halty et al., 2019). It is noteworthy that, although PC can directly improve actual performance, its effects are mainly realized through indirect paths.

Mediating Role of SC

It was found that SC plays a significant mediating role in the association between PS and SP. PS are typically demonstrated in the processes of analyzing problems, designing solutions, and implementing those solutions, while SC provides the necessary knowledge and skill support throughout these stages. Specifically, SC serves as a bridge for knowledge application, a foundation for practical operations, and a basis for reflection and refinement (Boelt et al., 2022; Stohlmann et al., 2012). It enables students to transform mathematical and technological knowledge into actionable problem-solving strategies.

During the problem-solving process, students must continually test and refine their solutions in practical settings. SC equips students with the skills required to carry out these iterations effectively. Proficiency in technological knowledge, for example, allows students to efficiently complete design and production processes, thereby improving their overall performance. Furthermore, SC supports reflection and iterative improvement. For example, when a design solution deviates from its intended outcome, students can rely on conceptual knowledge to reassess the problem and propose refinement strategies. This reflective process not only enhances the quality of solutions but also enriches understanding of STEM knowledge (Su, 2020).

CPM in STEM-PBL

The results of our study provide empirical support for the design of STEM education and offer novel perspectives on its practical application. Future STEM curricula should emphasize the interaction between PC and cognitive priming mechanisms, fostering supportive learning environments that promote holistic development in knowledge, skills, and attitudes. For example, Fan et al. (2020) emphasized the importance of clearly defining the scope of content knowledge in engineering-based STEM education to provide meaningful learning experiences. Undefined content knowledge could lead to ineffective assessments, ultimately affecting learning outcomes.

Furthermore, Stohlmann et al. (2012) also stressed the importance of integrating and applying knowledge across STEM disciplines while understanding the ability of students to avoid learning pitfalls. Dixon and Brown (2012) noted that inadequate guidance in applying STEM knowledge may hinder cognitive development and interdisciplinary learning among students, particularly if they lack foundational knowledge. Siew and Ahmad (2023) also concluded that insufficient guidance can impair the ability of students to effectively apply knowledge, experiences, and skills during practical tasks, weakening their problem-solving capabilities in STEM activities. These findings reveal several key characteristics of effective STEM instruction: An emphasis on affective development, the integration of multidisciplinary concepts and practices through problem-solving, and clear guidance in connecting relevant STEM knowledge while defining cognitive domains.

Conclusions and Implications

This study explored the interplay of STEM psychological capital (SPC), problem-solving skills (PS), STEM cognition (SC), and STEM project-based learning performance (SP) within a STEM-PBL framework themed on an IoT Smart Energy-Saving Houses. The results demonstrated that SPC significantly enhances PS, which significantly enhances SP through the mediating role of SC, offering a novel insight into psychological and cognitive factors in school STEM education.

These results demonstrate the synergistic interplay between psychological and cognitive factors in supporting lower-secondary school students' ability to apply interdisciplinary knowledge within project-based learning (PBL) contexts. Specifically, SPC fosters passion, perseverance, hope, optimism, and resilience, enabling students to navigate setbacks with confidence and maintain sustained engagement during complex STEM challenges—for

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instance, when designing IoT smart energy-saving houses, students with higher SPC were more likely to persist after initial design failures, adapting their strategies to meet project requirements. Simultaneously, SC enhances students' capacity to integrate mathematical and technological knowledge by facilitating the synthesis of abstract concepts (energy efficiency calculations) with practical applications (programming IoT devices), effectively bridging the gap between theoretical understanding and real-world problem-solving. As a result, students exhibiting elevated levels of SPC and SC demonstrated significantly improved performance in STEM projects, achieving more innovative and functional designs compared to their peers with lower scores. This integrated approach advances our understanding of how psychological and cognitive dimensions interact and also addresses a critical limitation in prior studies that often examined these factors in isolation, overlooking their combined effect on younger learners.

These findings offer implications for STEM education, particularly within the STEM-PBL framework with seventh-grade students in Taiwan. The results suggest that STEM educators should prioritize cultivating SPC by designing supportive learning environments that reinforce passion, perseverance, hope, optimism, and resilience—for example, teachers can implement structured reflection sessions after each design iteration, encouraging students to set small, achievable goals (fostering hope) and celebrate incremental successes (building passion), while providing emotional support to sustain perseverance during challenging prototype testing. Additionally, to enhance SC, educators can develop scaffolded activities, such as teamwork where students first simulate energy consumption scenarios using sensor data and then collaboratively redesign their house models, alongside incorporating peer feedback to refine technical skills. Consequently, this evidence-based, dual-focus approach complements existing STEM curricula by integrating psychological support and cognitive skill development from the outset, offering a practical framework for educators to adapt and implement.

Research Limitations

While our findings provide empirical insights into the psychological and behavioral mechanisms underlying STEM education, certain limitations warrant further exploration. First, the sample consisted of lower-secondary school students from a specific region, and data were collected in a localized STEM teaching context. Although this sampling strategy enhanced internal validity by controlling background variables, differences in teaching strategies, school resources, and educational policies may limit the generalizability of the findings. Specifically, this study focused on seventh-grade students in Taiwan, where cultural and educational factors may have influenced students' psychological capital and problem-solving behaviors. These research findings should be applied cautiously in different educational contexts, and future studies are encouraged to examine whether similar patterns emerge across diverse student populations and schooling environments. Another issue is that, given that the participants were seventh-grade students whose scientific knowledge was still in the early stages of development, the measurement of SC focused on specific performances in mathematics and life technology, emphasizing the application of subject knowledge. While this approach helped delineate the research scope and avoid overly general measurements, it may not fully capture characteristics of other STEM disciplines, such as physics or engineering.

Future Research Recommendations

Future studies may build on our findings to extend and deepen the research design and exploration of variables. For instance, expanding the measurement scope could provide a more comprehensive understanding of SC. Additionally, the interactions among SPC, PS, and SP were examined. While the cross-sectional design was appropriate for preliminary model validation, it does not allow for capturing the long-term developmental effects of SPC. Employing a longitudinal design in future research could provide deeper insights into changes across learning trajectories. Therefore, employing a longitudinal design in future research could track changes in students' PC, PS, and SC across semesters or academic years, verifying causal interactions among variables. Long-term observations could reveal how the cultivation of SPC enhances student comprehension, offering timely guidance for educational strategies. Additionally, future research could explore mechanisms within the integrative model to explore differences in learning processes among diverse student groups, providing empirical evidence for differentiated educational strategies in STEM education. These extensions would not only strengthen the explanatory power of the model but also enhance the practical applicability of the findings, offering theoretical support for the development and practice of STEM education.

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Declaration of Interest

The authors declare no competing interest.

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Appendix 1: The students' STEM psychological capital scale

Item
1. During STEM project activities, I do not feel discouraged by setbacks and rarely give up.
2. During STEM project activities, I often set goals but then switch to pursuing different ones.
3. I work diligently during STEM project activities.
4. I find it challenging to stay focused on difficult STEM projects.
5. Once I start working on something during STEM project activities, I won't stop until it's completed.
6. My interests in STEM projects (the topics I want to pursue) frequently change.
7. I am persistent and never give up during STEM project activities.
8. I was once very interested in STEM projects, but I eventually lost interest.
9. I am not afraid of setbacks when overcoming significant challenges during STEM project activities.
10. When I encounter difficulties in learning, I can find various ways to solve the problem.
11. I am currently actively pursuing my goals.
12. I can come up with several ways to achieve the goals I set for myself.
13. At this moment, I am steadily working toward achieving my goals.
14. I consider myself quite successful in learning.
15. There are many solutions to the problems I am currently facing.
16. In moments of uncertainty, I usually anticipate the best outcomes.
17. I always maintain an optimistic attitude toward the future.
18. I always look on the bright side of things.
19. I generally feel that good things are likely to happen.
20. When I face setbacks in life, I can always bounce back and keep moving forward.
21. I don't need much time to overcome stress.
22. I can usually recover quickly from a low point.

Appendix 2: The students' problem-solving skills scale

Item
1. I can identify the key points and priorities of a problem.
2. I can analyze the resources and constraints required to address a problem.
3. I can formulate predictive conditions and directions based on analysis results.
4. I can identify the direction for data collection.
5. I can gather information through various methods and channels.
6. I can analyze and filter accurate and helpful information.
7. I can convey design concepts using images, text, oral descriptions, videos, drawings, or prototypes.
8. I can develop diverse and creative design concepts.
9. I can share design concepts with team members.
10. I can present comprehensive and detailed design concepts.
11. I can use evaluation criteria to objectively judge and select the best concept.
12. I can clearly express specific design plans through text descriptions, sketches, orthographic projections, or models.

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Item
13. I can select appropriate materials and formulate production methods and procedures based on design concepts.
14. I can analyze potential issues and provide necessary assistance in production processes and material handling.
15. I can develop a team-based division of tasks based on a production plan.
16. I can follow designated methods and procedures to execute production tasks.
17. I can adhere to safety regulations during production activities.
18. I can effectively utilize available resources to produce a finished product.
19. I can correctly use materials, tools, and equipment to create a finished product.
20. I can document key problems encountered during production and effectively resolve them.
21. I can test whether the final product effectively solves the intended problem.
22. I can revise and adjust a product based on test results.
23. I can review process records and propose optimal revisions based on evaluation outcomes.

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